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Machine Learning in Estimating CO₂ Emissions from Electricity Generation

Marco Rao

Abstract

In the last decades, there has been an outstanding rise in the advancement and application of various types of Machine learning (ML) approaches and techniques in the modeling, design and prediction for energy systems. This work presents a simple but significant application of a ML approach, the Support Vector Machine (SVM) to the estimation of CO₂ emission from electricity generation. The CO₂ emission was estimate in a framework of Cost-Effectiveness Analysis between two competing technologies in electricity generation using data for Combined Cycle Gas Turbine Plant (CCGT) provided by IEA for Italy in 2020. Respect to other application of ML techniques, usually developed to address engineering issues in energy generation, this work is intended to provide useful insights in support decision for energy policy.

Keywords: CO₂ emissions, energy systems, machine learning, support vector machines, cost-effectiveness analysis, forecasting

1. Introduction

The science of decision support is foundational for every type of policy, and this work offer a proposal to analyze its role in energy policy.

An example of application of a particular machine learning (ML) technique to an energy policy problem is presented. It is important to understand the role of ML in energy and environmental analysis, for two solid reasons.

The first concerns the need to process large volumes of data and to elaborate and model complex relationships, typical of the energy analysis and of the environmental analysis. In this context, the use of AI (Artificial Intelligence) and machine learning is almost mandatory.

The second concerns the need to a concerted effort to identify how these tools may best be applied to tackle major problems of recent years, like climate change [1]: about this, CO₂ emissions is key variable that we must control to achieve the global objective of mitigating damage for humanity.

This work has a specific goal. Using known tools from the scientific literature on energy generation costs, we intend to show how the use of a machine learning technique (the support vector machines, SVM) can produce a more accurate modeling of these costs.

The link with CO₂ emissions is provided by the possibility of using the cost model in a cost-effectiveness analysis (C-E A), in which the cost is represented by

the Levelised Cost of Energy (LCOE) and the effectiveness is represented by the CO₂ emissions of the technologies considered per unit of energy produced.

The CO₂ estimation is then obtained by selecting the best generation options according to the C-E A results.

The meaning of this work is the following.

Imagine that you are an energy analyst, in the public or private sector, and you need to use only one or just few variable/s (such as a forecast on the cost of natural gas), to estimate the costs of an electricity generation technology.

This task can be accomplished using a cost model of electricity generation in which a single piece of information can vary, leaving everything else unchanged (or imposing a certain trend on it).

The metric used is the indicator LCOE (Levelised Cost of Energy) provided by IEA (International Energy Agency), using 2020 data.

Once you have obtained a certain level of accuracy in estimate of energy cost, it is possible to move into a context of cost-effectiveness analysis, in which the best energy option in terms of Incremental Cost-Effectiveness Ratio (ICER) was selected to produce energy and, finally, provide a certain level of CO₂ emissions for the time horizon in which such a technology is still the “best option”.

In other words, the estimate of energy cost and the cost-effectiveness analysis, allow us to trace the scenarios for electricity generation mix and, finally, calculate a quantitative forecast of the CO₂ emitted.

The proposed work just intends to show the application of one of the existing machine learning techniques to the estimation of the LCOE, starting from some explanatory variables.

A linear model (LM) and an SVM are compared in the prediction of the LCOE value for a combined cycle gas plant (CCGT) with a focus on the fuel cost, Operation and Maintenance (O&M) cost and CO₂ price using IEA data for Italy in 2020.

The work carried out intends to highlight the possibilities of applying machine learning techniques not only in the purely engineering aspects of energy systems, but also in the statistical-economic ones at a higher level of abstraction.

Some words about why to focus on power generation systems.

As countries work towards a low carbon world, it is crucial that policymakers, modelers, and experts have at their disposal reliable information on the cost of generation.

IEA [2] reports that the levelised costs of electricity generation of low-carbon generation technologies are more and more low the costs of conventional fossil fuel generation. Renewable energy costs continue their descent in recent years and their costs are now competitive with dispatchable fossil fuel-based electricity generation for many countries.

2. Methodology

This section presents the main tools used in this work: the LCOE methodology provided by IEA and the SVM, the used machine learning technique. Just before SVM presentations a very brief remind about ML and its use in energy systems and CO₂ emissions estimates will be provided.

2.1 Levelised cost of energy

The Levelised Cost of Energy (LCOE) is the selected tool to measure the cost of an energy unit produced by the considered technologies. LCOE is a methodology described in the joint report by the International Energy Agency and the OECD

(Organization for Economic Co-operation and Development) Nuclear Energy Agency (NEA) (now at the ninth edition in a series of studies on electricity generating costs) [1]. This report includes cost data on power generation from natural gas, coal, nuclear, and a broad range of renewable technologies.

The metric for plant-level cost chosen is the well-known levelised cost of electricity (LCOE) (IEA are now considering system effects and system costs with the help of the broader value-adjusted LCOE, or Levelised Cost of Value-Adjusted LCOE, VALCOE metric, here not considered).

The LCOE is widely considered as the principal tool for comparing the plant-level unit costs of different base load technologies over their operating lifetimes since indicates the economic costs of a technology family, not the financial costs of a certain projects in a certain market. Due to the equality between discounted average costs and the stable remuneration over lifetime electricity production LCOE recall the costs of electricity production in regulated electricity markets with stable tariffs than to the variable prices in deregulated markets.

Despite many limitations, LCOE has maintained its utility and appeal since it is a uniquely straightforward, transparent, comparable, and well understood metrics remaining a widely used tool for modeling, policy making and public debate.

The calculation of the LCOE is based on the equivalence of the present value of the sum of discounted revenues and the present value of the sum of discounted costs. Another way on the left-hand side one finds the discounted sum of benefits and on the right-hand side the discounted sum of costs:

$$LCOE = P_{MWh} = \frac{\sum (Capital_t + O\&M_t + Fuel_t + Carbon_t + D_t) * (1 + r)^{-t}}{\sum MWh * (1 + r)^{-t}} \quad (1)$$

where:

- P_{MWh} The constant lifetime remuneration to the supplier for electricity;
- MWh The amount of electricity produced annually in MWh;
- $(1 + r)^{-t}$ The real discount rate corresponding to the cost of capital;
- $Capital_t$ Total capital construction costs in year t;
- $O\&M_t$ Operation and maintenance costs in year t;
- $Fuel_t$ Fuel costs in year t;
- $Carbon_t$ Carbon costs in year t;
- D_t Decommissioning and waste management costs in year t
- P_{MWh} is equal to levelised cost of electricity (LCOE).

Eq. (1) is the formula used here to calculate average lifetime levelized costs based on the costs for investment, operation and maintenance, fuel, carbon emissions and decommissioning and dismantling provided by OECD countries and selected non-member countries.

2.2 Machine learning

Machine learning (ML) is the field of artificial intelligence (AI) that provide methods to learn from data over time creating algorithms not being programmed to do so.

The literature about ML is relatively recent but is so vast that only some hint to review works can be made here, as an access point to this world¹.

Machine learning approaches are normally categorized as in the follows.

¹ Here we just remind a recent review of the state of art in machine learning techniques [3].

Supervised machine learning, that trains itself on a labeled data set; **unsupervised machine learning** that uses unlabeled data with algorithms to extract the features required to label, sort, and classify the data in real-time, without human intervention; **semi-supervised learning** (SsL) namely a medium between supervised and unsupervised learning: SsL uses a smaller labeled data set during training and make classification and feature extraction from a larger, unlabeled data set; **reinforcement machine learning** is like supervised learning, but do not requires sample data for training (since using “trial and error” mode).

About the machine learning algorithms for use with labeled data the **regression algorithms** (as linear and logistic regression); **decision trees** (based on a set of decision rules to perform classification); **instance-based algorithms**: it uses classification to estimate how likely a data point is to be a member of one group, or another based on its proximity to other data points.

Methods based for use with on unlabeled data are: **clustering algorithms**: (like K-means, TwoStep, and Kohonen clustering); **association algorithms**: (that find patterns in data by identifying ‘if-then’ relationships namely association rules); **neural networks**: (that create a layered network of calculations featuring an input layer, when data in; one or more hidden layer, where calculations are performed; and an output layer. Where each conclusion is assigned a probability); **deep neural network** that uses multiple hidden layers, each of which successively refines the results of the previous layer. Deep learning models are typically unsupervised or semi-supervised. Certain types of deep learning models—including convolutional neural networks (CNNs) and recurrent neural networks (RNNs)—are driving progress in areas such as computer vision, natural language processing (including speech recognition), and self-driving cars.

In this work, the machine learning approach used is the SVM one.

SVMs² are machine learning algorithms built on statistical learning theory for structural risk minimization. In pattern recognition, classification, and analysis of regression, SVMs outperform other methodologies. The significant range of SVM applications in the field of load forecasting is due to its ability to generalize (also, local minima lead to no problems in SVM).

SVM was chosen, in this work, for the sake of simplicity, since the performed Support Vector Regression (SVR) [5], extremely easy to understand in comparing a traditional statistical tool with a competing machine learning based one.

Often, the available applications of SVM in the energy sector are oriented on the engineering side³ while in this work the approach is oriented in support decisions for energy policy field.

Using one of the possibilities offered by SVMs, namely the SVR, the follows show how it is possible to obtain more accurate forecasts of costs per unit of energy produced, using LCOE as a metric.

The best available accuracy is then used in a context of cost-effectiveness analysis.

In the following, a method to select among competing options (options that can be differ even for slight changes in some significant LCOE parameters), the one characterized by the best Incremental Cost-Effectiveness Ratio (ICER) is presented.

The possibility of making this choice during the lifetime of the plant leads to the possibility of identifying the best technology available, year by year, to get the corresponding profile of the associated CO₂ emissions.

² For a good introduction to this topic see [4].

³ See, for example [6].

2.2.1 Machine learning for energy systems and CO₂ emission estimation

The growing utilization of data collectors in energy systems has resulted in a massive amount of data accumulated (an increasing mass of smart sensors are now extensively used in energy production and energy consumption) leading to a continuous production of big data and, consequently, to a massive number of opportunities and challenges in decision support science.

Today, ML models in energy systems are essential for predictive modeling of production, consumption, and demand analysis due to their accuracy, efficacy, and speed or to provide an understanding on energy system functionality in the context of complex human interactions.

Salimi et al. [7] propose a comprehensive review of essential ML to present the state of the art of ML models in energy systems and discuss their likely future trends.

Machine learning was used for estimate CO₂ emission from energy systems in several context, using different approach. It is possible to recall, among an increasing number of works in recent years:

Leerbeck et al. [8] about flexibility of the electricity demand, a machine learning algorithm developed to forecast the CO₂ emission intensities in European electrical power grids distinguishing between average and marginal emissions in Danish bidding zone DK2;

Magazzino et al. [9] an investigation on the causal relationship among solar and wind energy production, coal consumption, economic growth, and CO₂ emissions for these three countries;

Cogoljević et al. [10] on the linkage between energy resources and economic development the focus of that work is to develop and apply the machine learning approach to predict gross domestic product (GDP) based on the mix of energy resources with a higher predictive accuracy;

Wu et al. [11] about proposing a standardized framework for estimating the indirect building carbon emissions within the boundaries of various types of Local Climate Zones (LCZs using a random forest machine learning method);

Mele and Magazzino [12] on the relationship among iron and steel industries, air pollution and economic growth in China (using a Long Short Term Memory, LSTM, approach);

Li et al. [13] on the forecasting of energy consumption related carbon emissions for the Beijing-Tianjin-Hebei region.

Huang et al. [14] on the uses of gray relational analysis to identify the factors that have a strong correlation with carbon emissions for China to reduce carbon emissions by studying prediction of carbon emissions (using LSTM).

Csillik and Asner [15] on the creation of an automated, high-resolution forest carbon emission monitoring system that will track near real-time changes and will support actions to reduce the environmental impacts of gold mining and other destructive forest activities for the Peruvian Amazon (using deep learning models).

Csillik et al. [16] on the use of a random forest machine learning regression workflow to map country of Peru by combining 6.7 million hectares of airborne LiDAR measurements of top-of-canopy height with thousands of Planet Dove satellite images into, to create a cost-effective and spatially explicit indicators of aboveground carbon stocks and emissions for tropical countries as a transformative tool to quantify the climate change mitigation services that forests provide.

Niu et al. [17] to determine whether China can achieve the commitment of reducing carbon emission intensity in 2030, through a general regression neural network (GRNN) forecasting model based on improved fireworks algorithm (IFWA) optimization is constructed to forecast total carbon emissions (TCE) and carbon emissions intensity (CEI) in 2016–2040.

2.3 Our methodology

The present work reports an experiment performed using a simple LCOE model, built according to basic methodology proposed by IEA. The performed experiment is simple and straightforward. Two energy scenarios were produced, one based on a certain hypothesis of change in the fuel cost, the other based on a hypothesis of change in fuel cost, O&M cost, and CO₂ price, for the CCGT type plant, over a period of 30 years.

In each scenario, a certain LCOE profile is obtained for the time horizon considered. A simple regression analysis is then performed on this variable, using as explanatory variables, first the cost of fuel, and then the operating costs.

The analysis is carried out both using a LM and the SVM, with further manual tuning of the last to improve its performance. The manual tuning for SVR was used for the sake of simplicity since the main goal of the study is to suggest the application of this ML technique to gain forecasting accuracy to use in the following phase, the cost-effectiveness analysis.⁴

To evaluate the accuracy of the forecast, the Root Mean Square Error (RMSE), the Mean Average Error (MAE) and the Mean Average Percentage Error (MAPE) were used.⁵

This simple test was performed to show the accuracy of the fuel cost and O&M cost as a predictor of CCGT LCOE.

Once established the best technique, the data from the two scenarios in a third scenario are modified, under certain hypothesis explained in the follows, to made a C-E A between a technology represented by IEA data and another of the same type with little changes in O&M costs. Using ICER as a winning criterion, it is possible to select the best energy generation option and, finally, to trace the corresponding CO₂ emission estimate trend over the plant's lifetime.

All the data coming from IEA [2].

The LCOE model.

First, a LCOE model based on IEA Eq. (1), with the following level of detail, was built.

The basic relationships of the model are:

$$PF = Power * 8760 * AVL * \frac{AAF}{100} * (1 - AuxP) \quad (2)$$

$$ws = 1 - wd \quad (3)$$

$$ks = krft + EMRP * B \quad (4)$$

$$i = wd * kd + ws * ks \quad (5)$$

$$d = i / (1 + i) \quad (6)$$

$$dfi = \sum_j 1 / (1 + i)^j \quad (7)$$

$$icfinal = icfinal + \left(\frac{ic}{CnsT} \right) * dfi \quad (8)$$

$$df = \sum_j 1 / (1 + d)^j \quad (9)$$

⁴ Indeed, manual tuning is often considered as one of the most significant choice [18].

⁵ See [19] for a complete discussion about the used metrics.

$$ic_{final} = ic_{final} + \left(\frac{ic}{CnsT} \right) * df_{i1} \quad (10)$$

$$df_i = \sum_j 1/(1+i)^j \quad (11)$$

$$Pro = Pro + PF * df \quad (12)$$

$$OM = ((FOM + VOM) * PF) * df \quad (13)$$

$$Fue = ((CFue) * PF) * df \quad (14)$$

$$CO_2 = ((PCO_2) * PF) * df \quad (15)$$

$$Cost = \sum_j (OM + Fue + CO_2) \quad (16)$$

$$Decom = n * Decom * Pro \quad (17)$$

$$LCOE = (Power * ic_{final} * 1000 + Cost + Decom) / Pro \quad (18)$$

Where:

CC	Cost of Capital (USD/MWh)
Power	net capacity (MWe)
AVLF _{min}	Average Load Factor min value (%)
AVLF _{max}	Average Load Factor max value (%)
AAF	Average Availability Factor (%)
AuxP	Auxiliary Power (%)
Lifetime	Time horizon of plant (years).
wd _{min}	min weight of cost of debt on total cost (%)
wd _{max}	max weight of cost of debt on total cost (%)
kd _{min}	min value of debt rate (%)
kd _{max}	max value of debt rate (%)
t _{min}	min value of taxation (%)
t _{max}	max value of taxation (%)
krft _{min}	min value of free risk rate (%)
krft _{max}	max value of free risk rate (%)
EMRP _{min}	min value of Expected Market Risk Premium (%)
EMRP _{max}	max value of Expected Market Risk Premium (%)
B _{min}	min value of Beta (%)
B _{max}	max value of Beta (%)
CnsT _{min}	min value of Construction Time (years)
CnsT _{max}	max value of Construction Time (years)
FOM _{min}	Fixed Operation and Maintenance Costs min (USD*MWh)
FOM _{max}	Fixed Operation and Maintenance Costs max (USD*MWh)
VOM _{min}	Variable Operation and Maintenance Costs min (USD*MWh)
VOM _{max}	Variable Operation and Maintenance Costs max (USD*MWh)
Cfu _{min}	min value of Costs of Fuel (USD*MWh)
Cfu _{max}	max value of Costs of Fuel (USD*MWh)
Eff _{min}	min value of Efficiency (%)
Eff _{max}	max value of Efficiency (%)
PCO ₂ _{min}	min value of CO ₂ price (USD*MWh)
PCO ₂ _{max}	max value of CO ₂ price (USD*MWh)
Decom _{min}	min value of Decommissioning (USD*MWh)
Decom _{max}	max value of Decommissioning (USD*MWh)

All other parameters are settled using the IEA values.

	Fuel Cost (baseline 45.5 USD/MWh)	O&M Cost (baseline: 6.99 USD/MWh)	CO ₂ price (10.1 USD/MWh)
Scenario 1	Linear decreasing of 2% per year except every 6 years	constant	constant
Scenario 2	Linear decreasing of 2% per year except every 6 years	Linear decreasing of 2% per year except every 6 years	Linear decreasing of 2% per year except every 6 years

Table 1.
Scenarios used for the regression of LCOE on fuel cost and O&M cost

We have set two type of scenario, basing on the following assumptions about certain variables of the model. The basic hypothesis is a constant decreasing of 2% for every variable changed, except every 6 years (a totally arbitrary choice), simulating an increasing amplification of this cycle (every 6 years, the percentage variation of the cost respect to the previous value is double than it and then is multiplied for the number of the occurring, so the first time at year 6, this value is roughly 4, namely 2% multiplied by 2 and then multiplied per variation 1).

Table 1 describes the hypothesis used in this first step of the analysis.

3. Results

Figure 1 shows the results obtained by performing a SVR about the data from IEA [1] for the first scenario considered (**Figure 2**).

The values of RMSE for the Linear Model (LM), the SVM Model Before Tuning (SVMBT) and the SVM Model After Tuning (SVMAT) are:

	RMSE	MAE	MAPE
Linear Model	1,30E-14	8,39E-15	8,39E-17
SVM	5,25E-01	4,01E-01	4,01E-03
Tuned SVM	1,74E-03	1,54E-03	1,54E-05

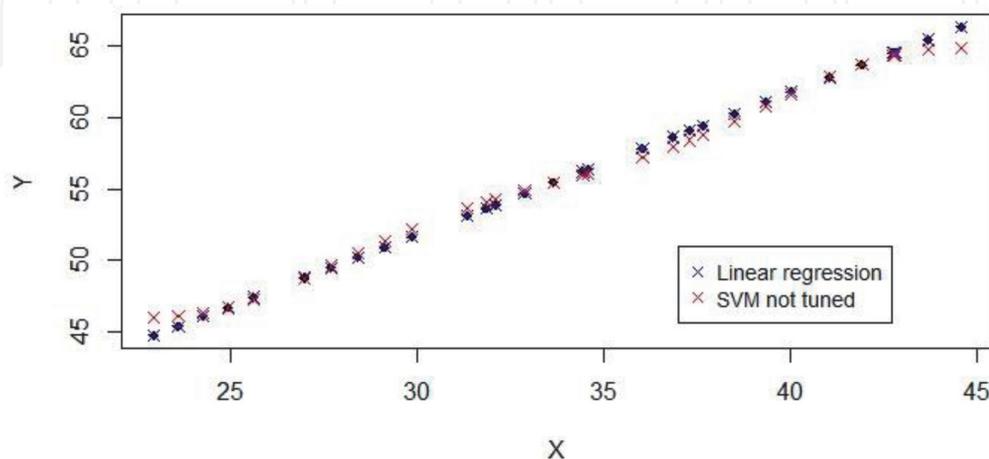


Figure 1.
Comparison between LM and SVMBT in predicting LCOE of CCGT technology for Italy (simulating data over lifetime of the plant - base data: Italy, 2020 - sources: IEA) - scenario 1 - Y = LCOE (USD/MWh), X = fuel cost (USD/MWh).

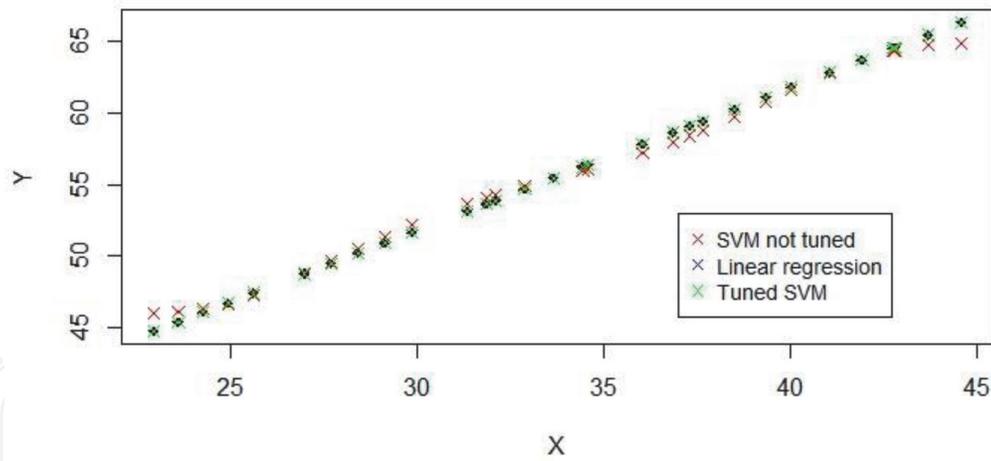


Figure 2. Comparison between LM and SVMAT in predicting LCOE of CCGT technology for Italy after tuning (simulating data over lifetime of the plant - base data: Italy, 2020 - sources: IEA) - scenario 1 - Y = LCOE (USD/MWh), X = fuel cost (USD/MWh).

with a clear improvement of performance of the SVM after tuning. The linear model since the strong relationships between the fuel cost and the LCOE is clearly preferable respect to the SVM (**Figures 1–4**).

The values of RMSE for the Linear Model (LM), the SVM Model Before Tuning (SVMBT) and the SVM Model After Tuning (SVMAT) are:

	RMSE	MAE	MAPE
Linear Model	3.87E+00	2.70E+00	2.70E-02
SVM	2.77E+00	1.59E+00	1.59E-02
Tuned SVM	2.61E+00	1.45E+00	1.45E-02

Recalling that in the second case the O&M cost was used as a predictor, we can more appreciate the gain in terms of RMSE obtained by using the SVM.

The increasing accuracy of the SVR respect to the LM, can be used to perform a CO₂ emission estimation in a cost-effectiveness analysis.

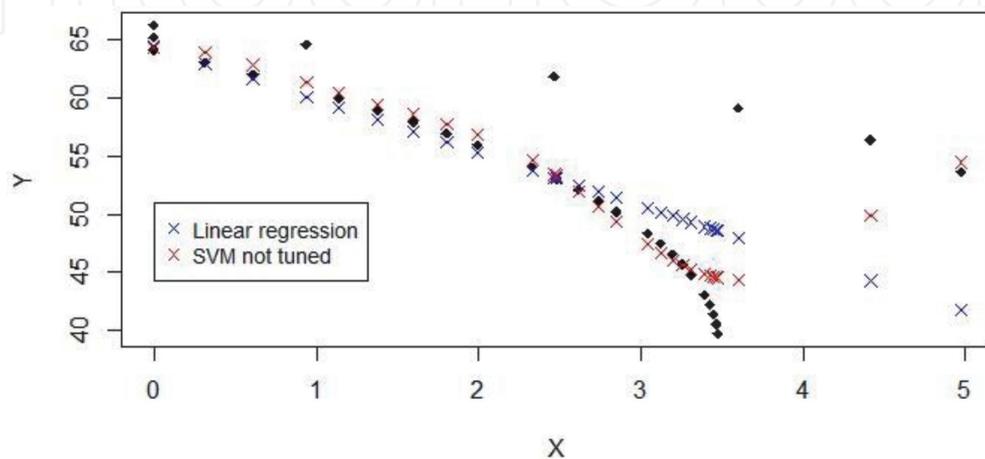


Figure 3. Comparison between LM and SVMBT in predicting LCOE of CCGT technology for Italy (simulating data over lifetime of the plant - base data: Italy, 2020 - sources: IEA) - scenario 2 - Y = LCOE, X = O&M Cost.

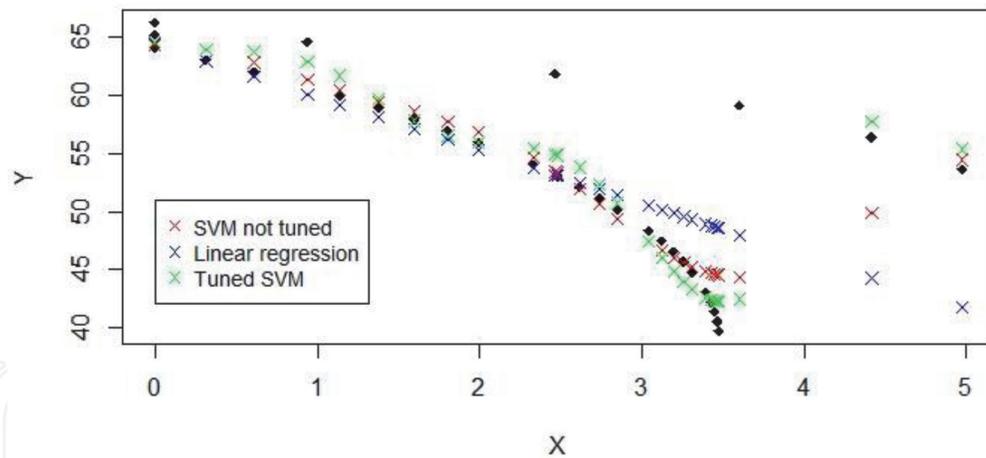


Figure 4. Comparison between LM and SVMAT in predicting LCOE of CCGT technology for Italy after tuning (simulating data over lifetime of the plant - base data: Italy, 2020 - sources: IEA) - scenario 2 - Y = LCOE, X = O&M Cost.

Let us look at a simple and plain experiment based on IEA data [2] for Italy, 2020 in the following scenario:

	Fuel Cost (baseline 45.5 USD/MWh)	O&M Cost (baseline: 6.99 USD/MWh)	CO ₂ price (10.1 USD/MWh)
Scenario 3	Decreasing of 15% at 15th year then linear decreasing of 1% until rest of the lifetime.	Decreasing of 15% at 15th year then linear decreasing of 1% until rest of the lifetime.	Decreasing of 15% at 15th year then linear decreasing of 1% until rest of the lifetime.

In scenario 3 we made a simulation basing on the hypothesis of a sudden shock for the three variables above reported in the 15th year, immediately followed by a linear decrease of them until end of the lifetime, starting from IEA 2020 data as a baseline value.

For scenario 3 the errors in predicting LCOE using O&M Cost over the considered time horizon are:

	RMSE	MAE	MAPE
Linear Model	4.25878	3.49147	0.03491
SVM	2.70117	1.52912	0.01529
Tuned SVM	2.58541	1.52378	0.01524

In Cost-Effectiveness Analysis it is possible to calculate the Incremental Cost-Effectiveness Ratio (ICER), used as a measure of cost the LCOE and used as a measure of effectiveness through the quantity of CO₂ emitted. The ICER can be used as a selection criterion between different options then, the winning options will be producing a certain level of emissions.

Now, let us imagine comparing two types of plants of the same technological family, in this case the CCGT. In this hypothetical exercise, the second type of plant is characterized by higher operating costs (+5% of the IEA base value).

In addition to this, let us imagine that the second type of plant has an average load factor of 94%.

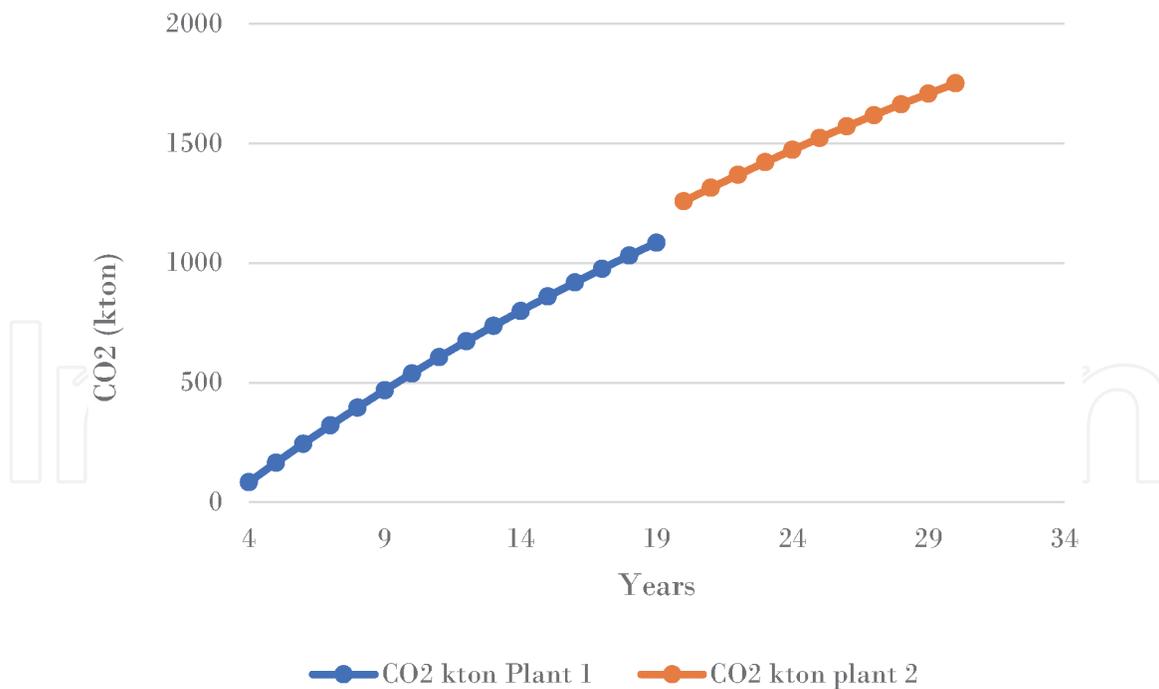


Figure 5.
CO₂ emissions from different kind of CCGT plants in scenario 3 (sources: IEA, 2020 + imaginary data).

Now, let us repeat the simulation performed for scenario 3 for the first type of CCGT plant (the real one), but only from the 20th year.

The meaning of this operation is as follows:

- to use systems with different characteristics (in this case we have changed the O&M costs and the load factor of a single technology family);
- to calculate the ICER corresponding to each plant in a defined time interval (in this case, from when the LCOE starts to vary);
- to calculate the degree of uncertainty on the value of the ICER thanks to the MAPE of the SVR, defining the variation range for the ICER⁶;
- to select the technology that has the lowest ICER and then we calculate the corresponding emissions over the time horizon considered;
- finally, to calculate the emissions profile corresponding to the winning technology, year by year.

The results are shown in **Figure 5**.

Figure 5 illustrates what happens using the ICER criterion as a selector of the winning generation option. For the first 20 years, the first type of installation is selected, and the corresponding emissions are those of the blue line. From 20 years of age onwards, using the ICER as a criterion means choosing the second type of plant and the curve that shows the new profile of the emissions is the orange one.

4. Conclusions

ML can help in providing accurate forecasts of CO₂ emissions from power generation, especially when we face simultaneous variation of major driver (like

⁶ Namely, $ICER_{max/min} = ICER \pm ICER * MAPE$.

fuel cost, operating cost of the plant and so on); only a little piece of the possible comparisons between traditional techniques and a particular ML method was shown, focusing on the better performance of the ML one (SVM) respect to the traditional one (the LM).

In our case, the performed step was:

1. improving LCOE forecasting performance,
2. comparing multiple competing options by use of the ICER in Cost-Effectiveness Analysis;
3. consider the uncertainty about ICER using the MAPE (in this case, but is just an option) calculated by SVM;
4. choosing the best technology and calculating the CO₂ emissions for it;
5. defining the trend of the CO₂ emissions in the lifetime of the plant by step 4.

Recalling that a basic LCOE model can be brought to a great level of granularity, it is easy to imagine how this type of analysis could gain in depth and significance if the required data are available. Indeed, also in case of missing data, significant simulation can be provided by using each available piece of information on energy costs.

The experiment performed was conducted at the highest level of simplicity to better focus on the reasons that suggest ML integration not only about the engineering features of electricity generation field but also in support decision tools about energy policy.

Conflict of interest

The authors declare no conflict of interest.

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References

- [1] Rolnick, D. and Donti, P. and H. Kaack, L.H., and Kochanski, K. and Lacoste, A. and Sankaran, K. and Ross, A. and Milojevic-Dupont, N., and Jaques, N., and Waldman-Brown, A., and Luccioni, A., and Maharaj, T., and Sherwin, E., and Mukkavilli, S.K., and Konrad P. K, and Carla Gomes, K., and Ng, A., and Hassabis, D., and C. Platt, J. C., and Creutzig, F., and Chayes, J. and Bengio, Y., *Tackling Climate Change with Machine Learning*, 2019
- [2] IEA, *Projected Cost of Generating Electricity 2020*, IEA, 2020
- [3] Saravanan and Sujatha, P., "A State of Art Techniques on Machine Learning Algorithms: A Perspective of Supervised Learning Approaches in Data Classification," *2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS)*, Madurai, India, 2018, pp. 945–949, doi: 10.1109/ICCONS.2018.8663155.
- [4] Wang, L. *Support vector machines: theory and applications*, Springer-Verlag, Berlin, 2005
- [5] Awad M., Khanna R. (2015) Support Vector Regression. In: *Efficient Learning Machines*. Apress, Berkeley, CA. https://doi.org/10.1007/978-1-4302-5990-9_4
- [6] Zendejboudi, A., Baseer, M.A., Saidur, R. Application of support vector machine models for forecasting solar and wind energy resources: A review, *Journal of Cleaner Production*, Volume 199, 2018, Pages 272-285, DOI: 10.1016/j.jclepro.2018.07.164
- [7] Salimi, M., Mosavi, A., Faizollahzadeh, A.S., Amidpour, M., Rabczuk, T., and Shamshirband, S., *State of the Art of Machine Learning Models in Energy Systems, a Systematic Review*, *Energies* 2019, 12, 1301; doi: 10.3390/en12071301
- [8] Leerbeck, K., Bacher, P., Grønborg Junker, R., Goranović, G., Corradi, O., Ebrahimi, R., Tveit, A., Madsen, H., *Short-term forecasting of CO₂ emission intensity in power grids by machine learning*, *Applied Energy*, Volume 277, 2020, DOI:10.1016/j.apenergy.2020.115527
- [9] Magazzino, C., Mele, M., Schneider, N. A machine learning approach on the relationship among solar and wind energy production, coal consumption, GDP, and CO₂ emissions, *Renewable Energy*, Volume 167, 2021, Pages 99–115 DOI: 10.1016/j.renene.2020.11.050.
- [10] Cogoljević, D., Alizamir, M., Piljan, I., Piljan, T., Prljčić, K., Zimonjić, S. A machine learning approach for predicting the relationship between energy resources and economic development, *Physica A: Statistical Mechanics and its Applications*, Volume 495, 2018, Pages 211-214, DOI: 10.1016/j.physa.2017.12.082.
- [11] Wu, Y., Sharifi, A., Yang, P., Borjigin, H., Murakami, D., Yamagata, Y. Mapping building carbon emissions within local climate zones in Shanghai, *Energy Procedia*, Volume 152, 2018, Pages 815-822, DOI: 10.1016/j.egypro.2018.09.195.
- [12] Mele, M., Magazzino, C. A Machine Learning analysis of the relationship among iron and steel industries, air pollution, and economic growth in China, *Journal of Cleaner Production*, Volume 277, 2020, 123293, DOI: 10.1016/j.jclepro.2020.123293.
- [13] Li, M.; Wang, W.; De, G.; Ji, X.; Tan, Z. Forecasting Carbon Emissions Related to Energy Consumption in Beijing-Tianjin-Hebei Region Based on Grey Prediction Theory and Extreme Learning Machine Optimized by Support Vector Machine Algorithm.

Energies 2018, 11, 2475. <https://doi.org/10.3390/en11092475>

[14] Huang, Y., Shen, L., Liu, H. Grey relational analysis, principal component analysis and forecasting of carbon emissions based on long short-term memory in China, *Journal of Cleaner Production*, Volume 209, 2019, Pages 415-423, DOI: 10.1016/j.jclepro.2018.10.128.

[15] Csillik, O. and Asner, G.P. 2020 *Environ. Res. Lett.* **15** 014006

[16] Csillik, O., Kumar, P., Mascaro, J. *et al.* Monitoring tropical forest carbon stocks and emissions using Planet satellite data. *Sci Rep* **9**, 17831 (2019). <https://doi.org/10.1038/s41598-019-54386-6>

[17] Niu, D. Wang, K., Wu, J., Sun, L., Yi Liang, Y., Xu, X., Yang, X. Can China achieve its 2030 carbon emissions commitment? Scenario analysis based on an improved general regression neural network, *Journal of Cleaner Production*, Volume 243, 2020, 118558, DOI: 10.1016/j.jclepro.2019.118558.

[18] Korovkinas, K., Danènas, P., Garsva, G., Support vector machine parameter tuning based on particle swarm optimization metaheuristic, *Nonlinear Analysis: Modelling and Control*, Vol. 25, No. 2, 266–281, DOI= 10.15388/namc.2020.25.16517

[19] Botchkarev, A. A New Typology Design of Performance Metrics to Measure Errors in Machine Learning Regression Algorithms, *Interdisciplinary Journal of Information, Knowledge, and Management*, Volume 14, pp. 045–076, 2019, DOI= 10.28945/4184.